Faster Information for Effective Long-term Discharge: A Field Study in Adult Foster Care

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A growing proportion of the population is elderly. With this aging population, an increasing challenge is placing patients into adult foster care facilities, which are small long-term care nursing facilities. A key challenge is the dynamic matching process between hospital discharge coordinators looking to place patients, and facilities looking for residents. This paper describes the design and implementation of a 12 month deployment to support decision making among a team of 6 social workers assisting in the discharge of 107 long term care patients across 1,047 potential care facilities. Our system collected vacancy and capability data from facilities over time through conversational SMS. We then process the data to provide call recommendations as to which homes might be best for social workers to contact. We show that our system had sustained engagement over the duration of the deployment and provide evidence of the impact that timely, accurate information has on easing long-term care patient matching. Overall, we demonstrate that platforms for information exchange – even absent algorithmic recommendation or matching – can increase matching efficacy. We further provide lessons for designing information collection systems and provisioning platforms in similar contexts.

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1 INTRODUCTION

The US population is aging; and while 88% of adults over 50 believe staying at home ("aging in place") is important, 19% believe their home is insufficient to age in place [29], and 3% of the 55 million adults over 65 live in nursing, residential or adult foster care homes [7, 11, 32]. This population experiences some combination of not having a family to help care for them, or the finances to stay at home, and typically requires a high level of medical care.

An especially important avenue to no longer aging at home is after a hospital stay: elderly patients are often unable to be discharged back home even if they no longer need acute hospital care, and must be *placed* in a facility before they can be discharged. This is a significant challenge for hospitals and patients: in November 2022, 35 medical organizations, including the American Medical Association, wrote to the Biden administration detailing "gridlock" in Emergency Departments, and a "public health emergency" in part due to the inability to discharge patients [21]. This paper discusses findings from a year long deployment to improve the process of discharging patients in need of long term care, from *hospitals* to *adult foster care homes*.

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The length of stay of patients in a hospital is an important metric: an occupied bed in a hospital can cost upwards of thousands of dollars per day, most often paid by the hospital [21]. Discharge is managed by discharge coordinators, sometimes called social workers – these coordinators are responsible for finding an appropriate facility to whom to discharge the patient. These discharge coordinators face burnout due to the demanding and challenging nature of their work. Oftentimes they have limited control over a patient's care, such as insurance coverage and care facility availability, meaning a large part of their work is in information discovery and communication. In addition to finding matches on availability and insurance coverage, information discovery is also motivated by the need to identify placements that are less likely to lead to readmission, which might lead to increased healthcare costs and reduced patient outcomes – motivating an inclusion of social and cultural factors in the placement process. These factors combine to make up an important and challenging job that can be fulfilling when a successful placement happens, but too-often, carries high levels of stress and ultimately, burnout.

On the other side, *adult foster care homes* must find suitable patients for their homes. In contrast to better-known nursing homes, adult foster care homes are smaller scale (often less than five patients at a time), less institutionalized facilities, often run by one nurse [18], that nevertheless provide nursing home level of care for their residents. However, finding suitable residents for these homes can be a challenging task – each home has its own specific capabilities and preferences, for example with respect to the medical severity of a patient. Empty beds or ill-matched patients have disproportionate impacts on such small facilities and their patients, compared to larger scale nursing homes.

These challenges motivate our twelve month deployment in Hawaiʻi to facilitate long term care patient discharge into adult foster care homes. We detail existing workflows for long term care patient placement into these adult foster care homes, in particular the work of calling homes. In our setting, discharge coordinators historically rely on data provided by the State Department of Health. This data principally serves to convey that a home is currently licensed to operate, and secondarily for the purpose of patient placement – for example, the data includes whether a home has a vacancy. As we'll show, this data is insufficient for effective matching: we find this is updated on average every 105.4 days. We show how the task of calling the correct home for a patient's placement is challenging, and in-part that this challenge can be alleviated with faster information update intervals.

We describe a deployed system built in collaboration with social workers and discharge coordinators at a state hospital and associated adult foster care facility operators in the community, to help ease the matching process by collecting updated information about their vacancies and capabilities.[1] We used hybrid computer-human SMS to ensure the accuracy and reliability of regularly surveying home operators for their status and capabilities, and compiled the resulting data to provide call recommendations for discharge coordinators and social workers to use.

Our study shows there was substantial engagement with the system throughout the population, both for individual surveys and over the duration of the deployment, indicating the potential for such systems to effectively collect and disseminate information. These homes frequently updated their information in the system, demonstrating the need for such systems and the desire of homes to participate.

This study provides evidence of the impact that timely, accurate information has on increasing matches between patients and small adult foster care homes. By reducing informational and coordination frictions, our system is able to improve patient placement workflows. We conclude by highlighting the lessons learned in designing information collection systems and provisioning platforms in similar contexts, as well as demonstrate the potential of information collection and sharing platforms to increase matching efficiency. More generally, we provide lessons for dynamic

[1]One of the authors has a vested interest in the system described in this study.

matching systems – even absent more sophisticated matching recommendations, there are large gains to be made by providing timely information to participants.

2 RELATED WORK

Foster and Long Term Care Placement. State funded Adult Foster Care (AFC) has its beginning in the late 1970's with pioneering programs in Oregon and Washington, and since then states have steadily adopted similar programs [18]. The growth of these homes have been accompanied by a budding set of research that has studied the unique challenges faced in AFC [15]. For example, Mollica et al. [18] provide guiding frameworks for state implementation as well as cover the varying state idiosyncrasies throughout the US. Limited work has looked at the factors associated with effective foster care *placement*. Still, adult foster care researchers have looked into resident perceptions about being placed in adult foster care, as well as factors in weighing the qualitative differences between nursing homes and adult foster care homes [27, 28].

To our knowledge, no work specifically addresses the placement challenges faced by facility operators and hospitals in long term care placement or discusses a potential intervention (let alone computational interventions). However, there does exist literature that studies effective *children*'s foster care placement. Zeijlmans et al. [37] details for example, major gaps in the "Decision-Making Ecology" of foster care placement, noting that there is a clear need for effective matching into foster care. Similar work has also looked at the risks of placement instability and the implementation of a web based matching system to inform placement decisions by assessing an appropriate level of care [19]. Most recently, Saxena et al. [30] review the use of algorithms in the US Child Welfare System, and emphasize the importance of utilizing salient social worker knowledge and employing context-relevant social work literature. Researchers have also performed qualitative studies that detail the role of trust in existing apprehensions of algorithmic decision-making in child welfare services [6]. Beyond foster care placement, decades long work has studied the enablement and use of data-driven healthcare. In particular, Sun et al. [34] details the reality that data-driven decision making in LTC delivery and management is ultimately contingent on a growing burden of work fronted by frontline care workers. This work burden includes for example aggregating sensor data and digitizing field notes about a patients level of care.

Our system is designed by centering these concerns on how data-driven and algorithmic systems affect the work (and work burden) placed on discharge coordinators. To this literature, we contribute an understanding of how out-of-date data leads to a phenomenon we call, "runaway labor" – the amount of work a discharge coordinator needs to do to place a patient sharply grows in the data's age. We further contribute a system design, to collect timely data from facilities in a manner that integrates with their existing workflows.

SMS in ICTD Contexts. We build and deploy an SMS system to collect timely data from facilities. Infrastructure deployment, especially in Information and Communication Technology for Development (ICTD) settings is difficult. As the Human-Computer Interaction (HCI) community has explored, adhering to existing workflows is important in the theory of change [16]. With the proliferation of cellphone technology, SMS has been extensively studied as a means of communication, both at a population level and more specifically in the potential of engaging at-risk populations.

SMS is especially important where mobile phone applications might prove to be an extensive barrier; for example, one area where SMS has been found to be particularly useful is in supporting unbanked populations [3, 12, 22, 25]. In many developing countries, a large portion of the population does not have access to traditional banking services. SMS-based banking has been implemented as a means of financial inclusion for these populations, allowing them to access basic banking services via text message. This has enabled millions of people to access banking services that were previously unavailable to them. SMS has also been studied with respect to improving community health outcomes. One example is the use of SMS to deliver health education and behavioral change messages to individuals with chronic conditions such as diabetes, hypertension, or HIV/AIDS, where messages aim to encourage healthy behaviors and promote adherence to medication regimens [17]. Other studies have used SMS to increase vaccine uptake [14], improve maternal and child health [10, 20, 23, 33], and provide support for mental health challenges [26]. The use of SMS has also been explored in the context of disease surveillance and outbreak response [35], where individuals can report symptoms and receive health information through SMS. These examples demonstrate the versatility and potential impact of using SMS to engage at-risk populations in various contexts.

In our context, SMS is ideal for demographic groups that may not be highly tech-savvy, such as older adults – thus increasing the likelihood of initial adoption – especially in comparison to mobile or web based smart phone applications.

One significant challenge described by prior work with respect to SMS is in the cost of the service; however, in the United States, SMS has become a widely used method of communication, with a high penetration of mobile phone usage and an abundance of unlimited texting plans. This characteristic makes SMS an attractive option for stakeholders in the adult foster care system, as it provides an accessible and efficient way to communicate with families, other foster care facilities, and social workers. The ease of use of SMS in the US is a key advantage, as it helps to fit into existing workflows and reduce the time and effort required to communicate.

Algorithmic Matching. The challenge tackled by our system is a *matching* one: we wish to efficiently connect patients to compatible AFC facilities that currently have vacancies. A long line of work in dynamic matching – for organ exchange [4], housing [36], ridesharing, etc – develops algorithmic matching approaches. Most related is a long line of work tackling refugee resettlement, wherein social workers use decision support tools to facilitate optimal placement of refugees to locations, to maximize objectives such as employment and personal preference [1, 2]. This literature describes a progression from a greedy batch matching process, that primarily seeks to burden share across locations, and eventually implements dynamic matching using predictions of placement success.

To this literature, the present work establishes that even absent sophisticated matching algorithms, there are substantial gains from accurate, timely information provision, as a decision-aid to participants engaging in a human-driven matching process. This work thus serves as a foundation to develop human-algorithmic collaborative approaches to matching in complex, sensitive, dynamic contexts.

Design of SMS querying systems. Key to our approach in providing up-to-date information to enable discharge coordinators is polling AFC facilities at faster intervals, and it is important to sustain engagement over time. One concern is "survey fatigue." Researchers have looked to effective gaps between surveys and the role time gaps between surveys might play in response rates [31], and have cautioned against "overexposure to the survey process" [24].

More specifically related is work surrounding SMS-based data aggregation. For example, work by Balabanis et al. [5] examines factors such as survey length and repetition, and trust in survey source and purpose, as factors that impact SMS survey participation. Moreover, they detail how lack of access to internet gives SMS a distinct advantage over web based surveys in reaching more diverse populations, in our case predominantly older female adult healthcare workers. In our setting this also reduces the need for extensive training, which is important for facilities that operate with limited resources and staff. Johnson et al. perform a randomized trial of an SMS survey on family planning participants in Kenya, studying similar factors such as survey timing, incentive, and engagement [13]. Crucially, they demonstrate a similar finding to ours: while an assumption with SMS is that users are enabled to answer at their convenience, in our case we found users either respond promptly, or not at all. We build on this work as another example of a low internet-utilizing

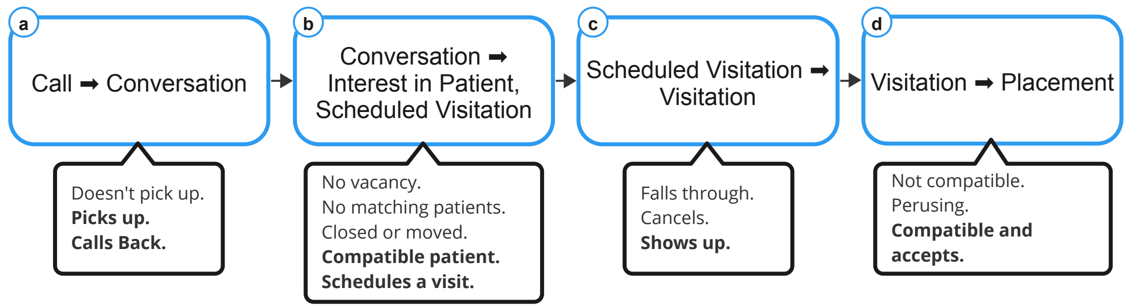

Fig. 1. An abbreviated four part workflow for discharging a medically-ready, insurance cleared, long term care patient.

population, displaying strong engagement over multiple SMS surveys, without direct financial incentives given to participants.

3 BACKGROUND

Here we describe how patient discharge occurs and discuss the status-quo state provided data. In our setting and to our knowledge, the state has offered updated data to support the growing need and supply of foster homes since June of 2014, principally to help verify legal operation of a home. Nonetheless, discharge coordinators have also historically used this data to identify facilities to call, including both adult residential, and foster care homes. At date of writing, the most recent dataset lists 1,240 adult foster care homes.

Discharge process. Once a patient has been financially and medically assessed as being ready for discharge from the hospital and is in need of long term care,[2] a discharge coordinator makes referrals to shelters, rehabilitation facilities, case management agencies, and other community partners – i.e., seeks to place the patient with one of these resources.

Figure 1 details the coordinator workflow. (a) They place calls to facilities (if they are able to reach them on the phone, itself a several-step process). Facilities with potential vacancies are identified using the state-provided data. (b) During a conversation, the facility may express interest in a patient and plan a visitation. (c) Not all planned visitations turn to actual visitations (there is substantial drop-off). (d) An actual visitation, in which the facility operator visits the patient in person, may result in a placement. There are numerous reasons why each stage may not proceed to the next stage. Discharge coordinators have indicated that, overall using state data, it might take upwards of 200 calls to get to a placement for a single patient. The deployment studied in this paper focuses on improving results in the first two stages (a) and (b): better, more up-to-date data, may result in more success in calling the correct facilities. We leave to future work the important challenges faced specifically in stages (c) and (d).

Description of historical state-provided data. To understand whether a data collection intervention is required and to inform system design, we conduct an analysis of state-provided historical data, collected via a state data portal. Our data includes 29 data refreshes identified between January 2014 and December 2022. We collect this data primarily via website archives on Archive.org, of which, October 2021 through December 2022 were real-time verified via weekly website polling for changes. While it is possible that Archive.org may have missed a posted update by the state, this seems unlikely as the archive recorded 93 snapshots over this timeframe, and we uncovered only 29 refreshes. Figure 2

[2]This process includes medical risk assessments and securing Medicaid Long Term Care insurance. [8]

shows the set of recorded snapshots, which shows irregularities at which updates were provided. The gaps between refreshes amount to: a) an average refresh rate of 105.4 days, b) a standard deviation of 98 days, and c) a minimum of 29 days, mode of 31 and two outliers of 365 and 395 days.

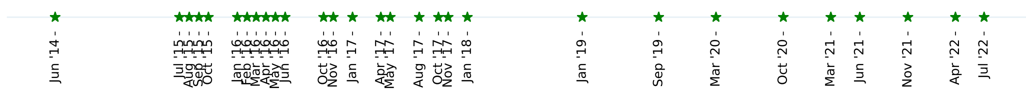

Fig. 2. Recorded Updates between 01/2014 and 12/2022. Mean gap: 105.4 days, SD: 98, minimum: 29, mode: 31, outliers: 365, 395.

Over time this data has been refined to indicate more precisely where homes are located, and what specific capabilities they have. In turn, this data has served not only in the interest of verifying legality of operation, but also in finding suitable long term care patient discharge locations, as the coordinators we have worked with explained. We further observe that the data has also seen several format changes throughout the years, suggesting qualitative changes in its utility for placement.

The first change in data format we note is between 2014 and 2016; before this time, license expiration was not included – we interpret the subsequent inclusion of this data as the intent to facilitate license verification. In the early data updates, we see 7 columns for facility location and contact, and a remaining 11 columns intended for placement such as "How many patients do you need?", “Will you accept all Medicaid?” and “How many Male,Female?”. We then note that 2017 onward, there were 12 columns for facility location and contact, one of these additional columns being an alternate phone number to contact the facility, and two of these being for date of certificate expiration. However, columns related to assisting with patient placement were reduced to one – simply indicating home capacities. While it is unclear exactly why this change happened, it is clear that the granularity of data provided for patient placement was reduced. These changes mark a potential shift in burden on discharge coordinators and social workers who may have relied on this data before these updates. It is also worth noting that this change corresponds with a decreased rate of the data being updated at all, as apparent in Figure 2.

Furthermore, in our later communication with homes, we learned that their listed data was out of date, that they had either retired, closed, no longer operated at the listed location, or were otherwise no longer operational. This occurred in 28 instances of participating facilities, and came in messages such as "Sorry, just retired." So while state provisioned data might have indicated a home was still certified, the unaccounted edge case of ceased operation within a certification period meant a home might still be needlessly called.

Effective matching requires access to accurate and up-to-date information about the capabilities and vacancies of adult foster care homes. We describe how this can be achieved through the use of data collection and sharing platforms, such as the hybrid computer-human SMS system discussed in this paper. By providing timely and accurate information, such provisions of data can increase the efficiency of the matching process and help to ensure that patients are placed in homes that are well-suited to meet their needs.

4 CONVERSATIONAL SMS SYSTEM DESIGN

Figure 3 is a flowchart detailing our system design. From left to right, we show a progression of automated steps, leading up to manual verification of updates, which in-turn drives automated compatibility matching and ultimately ranked call recommendation. Discharge coordinators access call recommendations on a user interface, where homes to call are ranked in order of ascending match count for each specific patient. This means that a home with no stated preference,

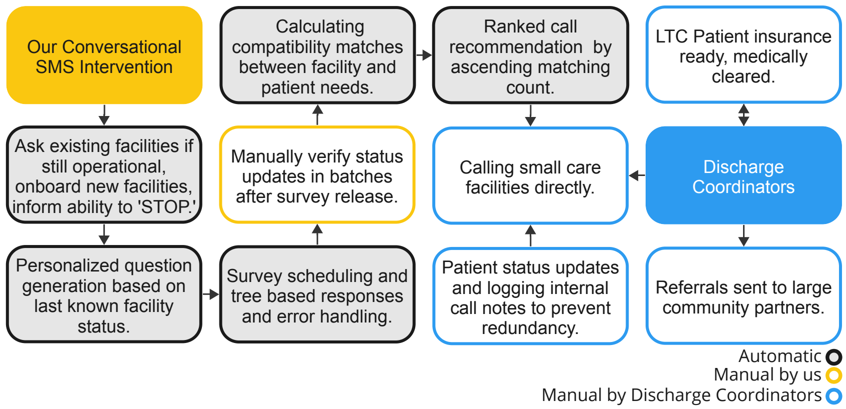

Fig. 3. Our system design and information flow.

is most likely to be ranked at the bottom of the list, and homes stating specific preferences that match with, e.g., only one patient, are ranked at the top of the list.[3] The selection of which home to call is ultimately left to the discharge coordinator, and they are enabled for example to invert this list. On this same user interface is the capacity to update patient statuses and leave call notes for specific homes who have been called about a patient, to help reduce redundant calls. The right-most column of this figure shows that discharge coordinators work both to: get patients medically cleared and their insurance ready, as we describe in Section 3. Lastly, referrals are also sent to community partners, such as shelters or case management agencies, to request that they consider accepting their patients.

Why SMS?. As described in Section 2, texting-based systems are a convenient avenue in the United States, especially for communities where smart phone applications may be a barrier. Our initial stakeholder discussions further sought out feedback with respect to mediums for communication and subsequently piloted with a small sub-sample of the population. We learned that SMS was a preferred and actively used form of communication among the population, and received an overwhelming preference for texting, compared to mobile based applications, or email, for example one respondent shared "I would have to ask my son to log me into his email." Discharge coordinators also confirmed that mobile phone contact was their most effective means of directly contacting facility operators. We subsequently used an external service to identify SMS-able phone numbers from the roster of foster home operators, which resulted in our omission of 165 of 1,240 adult foster care homes. In our initial survey sampling with 57 homes we found a high response rate of 64% over a 24 hour period, and in our findings we show similarly high response rates, received quickly, sustained over the duration of our deployment.

Question finding. Part of these initial stakeholder discussions also sought to identify questions being asked by stakeholders about one another, we identified three sources of questions: what *care facility operators* want to know, what *discharge coordinators* are most often asked for, and what level of care is determined by a risk evaluation regularly conducted by *social workers* to secure health insurance. Each of these sources of questions have their own set of forms that each party fills out, which discharge coordinators and facility operators helped us rank in importance. This included

[3]We note that the design of this ordering is important, and the subject of future work.

in order of importance: 1) vacancy, 2) insurance provider 3) patient behavior, 4) weight and 5) sex – as well as a long tail of less ordered, though nonetheless important factors such as level of ambulation, bed transfer and dietary needs. For the purposes of this study we examine vacancy, weight and sex as changing factors.

We use this queue of importance to progressively roll out and request survey updates on separate survey dates. As illustrated in the first column, second row in Figure 3, these surveys all began with an opt-in and explanation of how to opt-out after opt-ing in along the lines of: "Welcome to [this] SMS service for care facilities. At any moment you can unsubscribe by replying with 'stop'. Please text '1' to begin." This is in accord with well established practices in automated telecommunications messaging [9]. We subsequently ask in every survey to confirm the status of their vacancy or lack thereof, and each iterative survey contains a question specific to their status with respect to the queue of questions. Surveys are then scheduled with input from discharge coordinators regarding their rate of saturation of the last set of data. Conversations over SMS are then automated, for example with error handling for cases such as a blank received response triggering a request to clarify.

Hybrid Computer-Human SMS. While a significant portion of this survey deployment is automatic, a similarly significant portion is enabled by manual, hybrid computer-human SMS, noted in the second row and column of Figure 3. As described in prior work [23], hybrid computer-human SMS refers to messaging that combines automated and manual processes. In our setting, population-wide outbound surveys are automatically triggered, with personalized messages being generated based on a finite set of home capabilities, where the responses to these messages are analyzed by a human to help determine, in our example, the next facility capability question to ask. The degree of automation and manual intervention can vary depending on the specific use case. For example, in some instances, the human may only be involved in certain stages of the conversation, while in others they may be constantly monitoring and guiding the conversation. This information is then processed and analyzed automatically, but with the option for human interaction to verify or provide additional information as needed. This hybrid approach afforded us efficient data collection, while still maintaining the accuracy and reliability of traditional human-led data collection methods.

We employ hybrid computer-human SMS, primarily as a means of verifying that updates to a facility status are being conveyed to social workers correctly – and in some cases where error handling was insufficient to process a facility response, a human would follow up with a clarifying question. We differentiate our hybrid approach as 'automated' and 'manual' in Figure 3, to delineate how we facilitate this hybrid approach. The manual work then feeds back to update facility status and subsequently matching and call recommendations in the automated steps.

Critically we also outline on the right two columns of our system design the manual work conducted by discharge coordinators that lead up to their use of our call recommendations. This includes both seeking out placement referrals from other community partners, such as shelters, rehabilitation facilities and case management agencies – as well as updating patients and their needs and keeping internal call notes on our platform with respect to calling facilities sourced through our SMS surveys. We discuss further in findings how throughout our deployment, 107 patients have been uploaded in this same platform, and subsequently discharged.

5 SYSTEM EVALUATION AND FINDINGS

We investigate the potential for utilizing SMS technology in the adult foster care patient placement process to produce more timely, informative data. In particular, we ask: (1) Do people use our system, i.e., are SMS surveys accepted by the stakeholders involved, and if so, would the level of engagement decrease over time? What factors would play a role in determining engagement? (2) What does the collected data imply about how quickly facility vacancies and preferences are changing over time? (3) Would more timely data provided by our system improve downstream outcomes, such as the number of calls needed to discharge a patient? By addressing these research questions, we aim to gain insight into the feasibility and potential impact of using SMS technology in the adult foster care patient placement process.

Data description. In this section, we primarily use data from our conversational SMS system. From our analysis of state data, we find 1,840 unique total homes ever listed, growing steadily since the July 2014 update we identify, of 300. Not all homes remain active throughout the period; for example only 1,240 homes are open in the latest update. Of these open homes, we are able to message 1047 homes, as these homes provided mobile numbers (as verified by an external service). We sent out 16 waves of surveys over a year, totalling 37,402 messages and 8,014 received messages. We manually processed the responses after each survey wave, updating the covariates we detail in Section 4, for each responding home. In this paper, we analyze the following characteristics of each response: response time, whether the home updated their vacancy status, and whether they updated their preferences for patient sex and weight.

5.1 System usage

We begin our analysis by showing that our system is used, both by facilities and hospital discharge coordinators. We then analyze this usage in more detail, concluding that *community alignment matters*: it is essential to design an information gathering system that integrates with existing workflows and prioritizes important information.

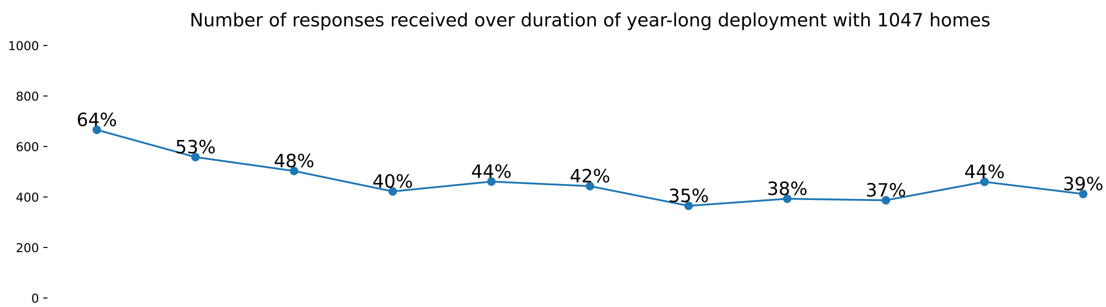

Fig. 4. Sustained Engagement with 1047 Homes

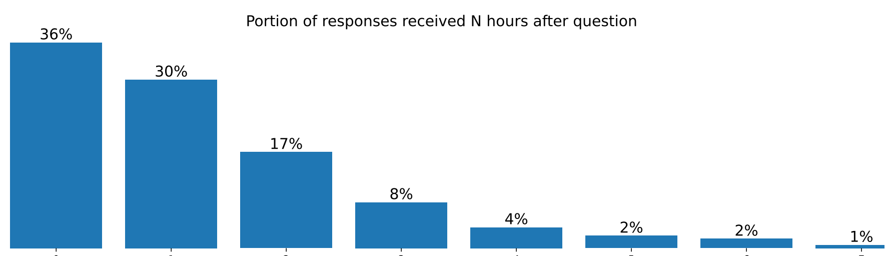

Fig. 5. Majority response within first two hours.

Overall usage and qualitative feedback. We observe sustained, fast engagement throughout our deployment: 99% of messagable facilities responded at least once across the deployment, and on average about 40% of all facilities responded to a single survey; Figure 4 shows that this usage is sustained over the length of the deployment. Furthermore, 83% of responses are received within the first three hours after a survey is sent, as shown in Figure 5.

Qualitative feedback provides evidence that our system is useful and is used to inform calling. Our discharge coordinator participants have indicated that our data has completely replaced state data for the purpose of deciding which homes to call, though other channels still contribute to sourcing potential placement locations, such as case management agency referrals or inbound community cold calls. Discharge coordinators have also described calls based on our data as effective, having stated they "found several accepting [homes] from [this platform]." Home operators have have also shared largely positive sentiment, for example 22% of all received messages containing "thank".

The discharge coordinator UI described in Section 4 further provides evidence of usage. There have been 150 patients recorded in the system, 107 of which have been discharged. Discharge coordinators have confirmed that at least 1/3 of these were placements to homes first contacted via our data; the original source of the remaining 73 patients is unknown, and facility placements may have been first contacted via other channels discussed in Section 4. [4]

Taken together, this evidence suggests that our data is indeed being used to inform calls, which contributes to further system usage: discharge coordinators are calling homes, and so home operators observe that their texts are informing their being called.

What factors contribute to sustained, quick responses?. We further observe several contributing factors to engagement: message timing, message personalization, ease of confirmation, and what kind of information homes wished to communicate.

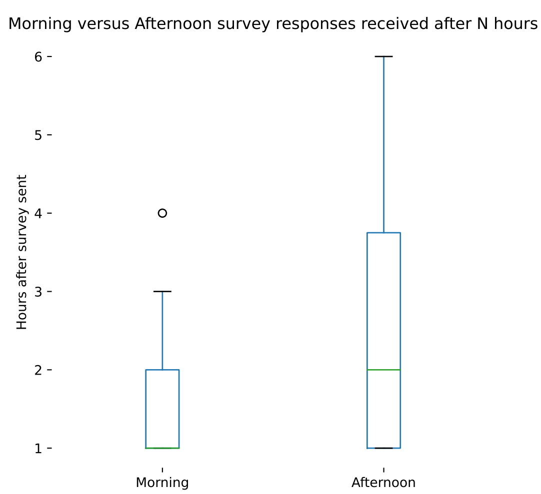

Fig. 6. Better engagement identified during morning hours, wherein not only did we see a greater concentration of responses in the morning, but we also saw a net average increase: on average, we receive responses from 401 facilities when surveys are sent in the morning versus 336 facilities when surveys are sent in the afternoon. Note that we cannot yet make causal claims regarding response rates, as survey timing was not randomized and we instead prioritized morning communication.

[4]It is important to note, however, that discharge broadly is a multifaceted and dynamic process, with many steps beyond an original call. Future work should concretize causal claims about the efficacy of improving the first stage of this process, within the broader system.

Motivated by the need to align system design with existing workflows (which itself motivated the selection of SMS as a communication channel), we analyze whether survey response variance across waves is due to message timing, a factor discussed in numerous prior works [5, 13, 24, 31]. Figure 6 shows that in our study we observed more and faster response rates for messages sent in the morning, with responses decreasing and slowing down as the day progresses. This finding is consistent with the work day of a home operator: once the day has begun, patient care work becomes more pressing than engaging in a text survey, and is consistent with prior work demonstrating that generally SMS participants in similar contexts will either respond promptly or not at all [13].

Next, we observe that users responded to personalized status updates as opposed to form messages. In particular, we ask directed questions such as "Our last update from you was the following", as opposed to: "Do you have any vacancies?" This personalization allowed users to see that their messages were in-fact being stored and that they had a status they could update, meaning their survey answers were not just being ignored. When their status from the previous survey is mirrored back to them, home operators often corrected their status, for example with “actually no longer medicaid.” We further provide homes the capacity to respond by simply saying “confirm”, to explicitly confirm their status. We found that this automation had a high usage rate: of the population stating their status had not changed, 40% made use of this “confirm” option.

Finally, we note that homes do not just respond when they have a vacancy – many respond to confirm a lack of a vacancy. Among homes responding after not responding for two or more survey periods (which would be on average 42 days), only 10.8% responded to state they now had a vacancy and the other 89.2% confirmed that they were full.

Together, this evidence (1) establishes that our system is being used to inform call decisions; and (2) suggests particular aspects of our system design that leads to higher usage rates. We note, however, that we did not systematically run experiments with various system designs – we cannot establish causal relationships between system design specifics and response rates; we leave such experiments for future work, guided by the above insights. We further note that participants also asked for further features, such as to add an ability to *schedule* calls and visitations over SMS to "make the search more efficient", toward the latter steps in the workflow detailed in Section 3.

5.2 Data content and underlying vacancy changes

Above, we establish that the system is *used* in terms of overall messages and responses. Here, we detail what the responses indicate about the system: in particular, how often vacancies and preferences change. In the next section, we will use these estimates to calibrate simulations for the comparative effectiveness of our data and the historical state provided data.

Change in home vacancies over time. At each wave, responding homes primarily responded with whether they have a vacancy for a patient. Figure 7 shows each response for each home over survey waves: whether homes responded, and how many vacancies they had. On average, about 55.4 homes indicate a vacancy during each survey response. Note that in our data provided to discharge coordinators, we impute missing vacancy data at time of last wave to a 0, indicating no confirmed vacancy; this choice enables discharge coordinators to prioritize calling homes that are most likely to still have a vacancy.[5] For homes, it requires them to reconfirm already provided vacancies – this requires

[5]We note that this choice has tradeoffs: it ensures higher-fidelity data for discharge coordinators.

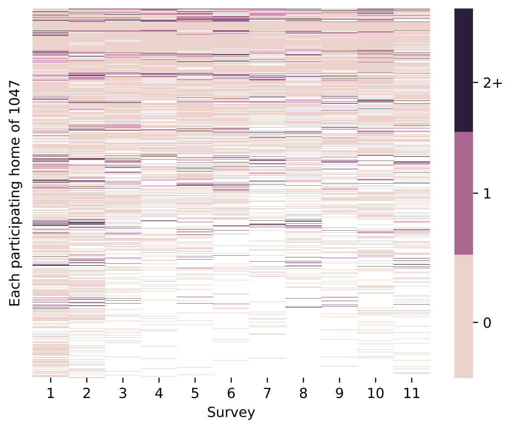

Fig. 7. Stated number of vacancies over time, for each home. White represents no response by the home for that survey.

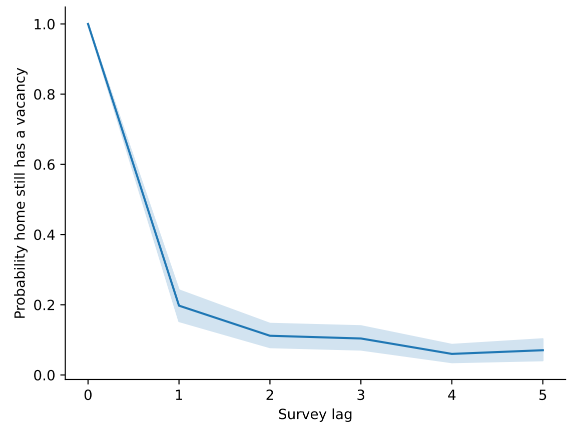

Fig. 8. Given that a home states a vacancy in some survey, the probability that the home also states a vacancy τ surveys later.

platform engagement, which may lead to accurate information but also burden homes. Designing optimal contact rates is an important avenue for future work.

How long do vacancies last?. In this system, vacancies are filled quickly. Of the average 55.4 homes that indicate a vacancy during a survey, only about 11 also confirm a vacancy in the following survey; a further 20 such homes respond to indicate that they no longer have a vacancy. Figure 8 further shows the *conditional autocorrelation* for vacancies for each home across surveys: given that a home has a stated vacancy at a survey, what is the probability that they state a vacancy τ surveys later – only about 20% of vacancies last to the next survey, and about 10% last 2 surveys. We note that this quick churn (as surveys are on average about 21 days apart, compared to the state data update frequency of 105.4) suggests that a data update rate of 105.4 days is insufficient to guide calling decisions: far before the data is updated, listed home capacities would no longer be informative. We note that non-response, and our imputation of missing data to "0," may bias these calculations downwards.

Change in other preferences. Beyond vacancies, home operators also express and change their capabilities and other preferences. Here, we analyze preferences for patient sex or weight. We note that these preferences can change over time; for example, one home operator changed a preference to not take on heavier weight clients, "due to recent pregnancy." These preferences are thus important to communicate to discharge coordinators attempting to place patients. In our data, 289 homes stated explicit sex preferences, and on average we saw 6% of this population change their preference once. Meanwhile, 340 homes stated weight preferences, with an average of 10% of this population changing their preference once during the deployment.

Together, this data suggests that the underlying preference and vacancy data is important, differs among facilities, and is subject to change. Discharge coordinators who do not have access to such timely data will not effectively be able to prioritize homes for patient placement.

5.3 Modeling Patient Matching and Efficient Labor

The above analyses demonstrate that underlying facility vacancies and capabilities both update faster than can be tracked with existing state data, and that our system has relatively up to date information. These findings are *suggestive*

Algorithm 1 Patient Placement Simulation

Data: Ground Truth Vacancies and Capabilities Y, Knowledge of Ground Truth $\hat{Y}$, List of Patients $(\theta_0, \theta_1 \ldots \theta_N)$

function PLACEMENTSIMULATION(patients, facilities, data refresh τ)
  Sort $\hat{Y}$ by descending vacancies (e.g. 1, 1 ... 0, 0)
  for patient in patients **do**
    Set matched = False, update ground truth, Y
    if patient = increment of τ **then**
      Perform knowledge refresh: set $\hat{Y} = Y$; re-sort by descending vacancies
    while not matched **do**
      Call next facility from $\hat{Y}$ where the facility-patient pair is compatible
      if Facility has a vacancy **then**
        Assign facility to patient and update $Y, \hat{Y}$
      Update facility state and knowledge for called facility
  Return list of calls performed per patient

of the new system providing value to discharge coordinators toward LTC placement efforts – up-to-date, accurate information should lead to higher call efficiency. In this section, we seek to formalize and quantify this effect, through a *calibrated simulation* of how discharge coordinators call homes to match patients. We demonstrate that slow refresh rates leads to "runaway labor" – while initially, stale data may not severely impact operations, relying on data that is too stale means that discharge coordinators may eventually call homes essentially at random.

Simulation description. Our simulation is detailed as Algorithm 1. The simulation proceeds over time, with N facilities, each with at most one vacancy (guaranteeing at least one facility that has a vacancy). Each time step (day), the true status of each facility (both vacancy status and patient preference) may update. Whether they have a vacancy is updated with probability p (otherwise, their status remains the same as the previous time step). Whenever their status is updated, they have a vacancy with probability q, and no vacancy otherwise. Preference updates are analogous. However, the information system used by discharge coordinators does not have perfect data: rather, the information system receives a knowledge refresh every τ time steps. At each time step, a discharge coordinator is attempting to place a single patient. They do so using the latest data that they have available, calling only facilities that they believe have a vacancy and have preferences that match the patient.

We calibrate the parameters to the data from our system. We set $N = 1,047$ facilities, with probability of a vacancy at $q = 0.05$ (as, at any given time, about 55.4/1,047 facilities respond that they have a vacancy). Vacancy update probability p is set to be consistent with Figure 8, in which about 20% of facilities that have a vacancy at day t still have a vacancy about 21 days later at day $t + 21$: i.e., p is set to be the solution of $(1-p)^{21} + (1-(1-p)^{21})q = 0.2$, implying $p \approx 0.08$.[6] For simplicity, we just model sex preferences, and model these preferences as static: 60% of patients are men, 40% are women; 80% of facilities have no sex preference, while 13% prefer females. Finally, we simulate two data refresh rates: every 21 days (matching our system), and every 105 days (matching the mean update cadence for the state data).

Simulation results. Figure 9 shows how average number of calls made (across multiple simulation runs) over time, at different refresh cadences. With fresh data (right after a data refresh, as indicated by the striped vertical lines), the discharge coordinators only have to make a few calls, as the facilities who had a vacancy at the last refresh still likely have a vacancy. As the data grows stale, however, the number of calls required to successfully place a patient grows rapidly, which we term as "runaway labor." Eventually with stale data, the discharge coordinators are calling essentially

[6] Either this facility never had their vacancy status updated, or had their status updated at least once and the last update led them to having a vacancy.

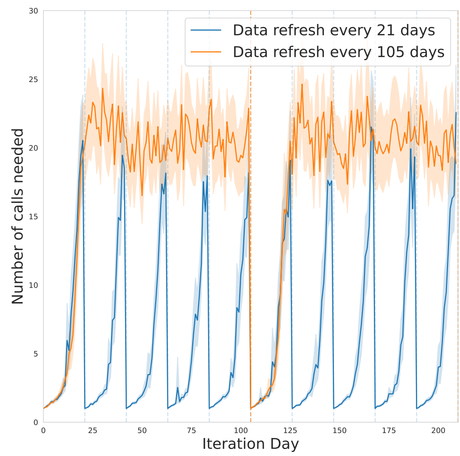

Fig. 9. Via simulation, the expected number of phone calls as a function of data refresh rate. Overall, the expected number of calls with a refresh rate of 21 days is 5.9 calls/patient. With a data refresh rate of 105 days, it is 17.7 calls/patient.

at random (which would have a call success rate of about 5%, or 20 calls until a home with a vacancy is found). Discharge coordinators note that in practice, they experience far greater call counts, upwards of 200 per patient, which we note is due to our simulation not taking into account factors discussed in the background such as having a visitation fall through, or other facility preferences preventing a match. Overall, more timely data leads to a factor of three reduction in the number of phone calls needed between discharge coordinators and facilities.

6 DISCUSSION

This paper explored the impact that delivering faster information can have on enabling effective long-term care discharge. We examine the impact that our SMS-based deployment over 12 months had on the discharge of 107 long-term care patients across 1,047 adult foster care facilities. We detail the reality of "runaway labor" associated with low-quality data, and demonstrate that human-algorithmic collaborative approaches that also account for integrating into existing workflows, such as our hybrid SMS system, can have a significant impact in easing frontline healthcare burdens. Moreover, to our knowledge we contribute the first of this early foundation toward effective adult foster care placement. We leave several areas for future work for example with respects to better inclusion of those also unable to use SMS, in constructing more robust call ranking, and identifying barriers to successful foster care visitations.

Our work highlights early signs that faster information may enable effective long-term-care discharge and patient placement, and while we look to prior work that has found tremendous success in deployments of matching systems across large populations for effective resource allocation, we remain nonetheless sensitive to important considerations surrounding algorithmic trust in similarly sensitive contexts. We note that our study would not have been possible without close partnerships with and centering of the lived-in experiences of front-line workers. Ultimately deciding where to discharge and place a patient for long-term foster care is a complicated task, and identifying an objective function for optimal resource allocation continues to be a challenge in similar work. We demonstrate nonetheless the impact that relatively modest data gathering approaches can play a significant role in supporting and augmenting decision making among front-line healthcare work.

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